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Investigation of alternate behavioural frameworks for mode choice decisions of workers in Chennai city

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Abstract

This study investigates the use of alternate behavioural frameworks namely – random utility maximization (RUM), random disutility minimization (RDM), random regret minimization (RRM) and composite decision rule (CDR) framework with respect to mode choice behaviour of workers in Chennai city. Most mode choice studies assume RUM as the inherent decision rule. However, this framework has been criticized due to its inability to represent non-compensatory behaviour, risk aversion and regret in choice. The multinomial logit model, used to capture utility maximization, suffers from the Independence from Irrelevant Alternatives (IIA) assumption, in contrast to the other frameworks. Alternative frameworks such as "Disutility minimization" and "Regret minimization" have been proposed separately in the literature. However, these studies have not compared alternate behavioural frameworks using empirical data. Further, the role of subjective factors on mode choice has not been analysed in these studies. It is also interesting to examine the variation in the effect of explanatory factors across these decision frameworks. Due to the absence of comparative analysis, this study is motivated by the need to understand the extent to which mode choice involves non-compensatory behaviour, the degree of asymmetry between utility and disutility, and role of risk aversion and regret in mode choice decisions, particularly in the Indian context. A better behavioural understanding using suitable modelling frameworks can lead to more accurate mode share forecasts and has important implications for evaluating urban transport plans and policies.

Keywords: Utility maximization; Regret minimization; Disutility minimization; Decision rule; Behavioural framework

1. Background and Motivation

Mode choice affects the vehicular demand for travel by personal vehicle, public transit and non-motorized modes. Thus, it has significant influence on sustainability, air-quality, congestion and system operating cost etc. Alternative

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decision rules may be used when an individual chooses his/her mode. A variety of decision rules are known which could be broadly categorized as fully compensatory, non – compensatory and semi compensatory in nature.

A fully compensatory decision rule is one where the poor performance of an attribute can be compensated by good performance of an equally important attribute. In contrast, in the semi-compensatory rule, this type of compensation is only partly possible and in a non–compensatory rule, the shortfall in one attribute can't be overcome by an improvement in another, regardless of the magnitude of improvement. Key notion in semi-compensatory rules is the notion of regret that a decision maker experiences with an alternative due to poor performance of an attribute. This regret can't be nullified completely by a good performance of an equally important attribute, and hence the individual settles down for a trade-off between these attributes and arrives at a choice. On the contrary, fully compensatory decision rules advocates that an individual would completely recover from this regret due to good performance of an equally important attribute.

Decision makers tend to become risk averse when faced with situations with high uncertainty (Chorus et al., 2012). Risk aversion is the reluctance of a person to accept an alternative with an unreliable performance on one or more attributes as compared to another alternative which is more reliable, but perhaps has a slightly poorer performance on those attributes. The RUM framework, which is fully compensatory in nature, doesn't account for this aspect of decision making behaviour. Further, decision makers may associate similar characteristics with respect to different alternatives (e.g., crowding in bus and train or door-to-door accessibility with car and two-wheeler) thus making them correlated. However, the multinomial logit model (MNL), the workhorse of RUM – which maps to the fully compensatory decision rule leads to the restrictive Independence of Irrelevant Alternatives (IIA) assumption. This assumption is likely to be violated due to the common unobserved attributes shared by different modes.

Although the assumption of fully compensatory decision rules could lead to biased forecasts as discussed above, there have been only a few studies which have considered alternate behavioural frameworks to represent decision making (These are discussed in Section 2). However, the focus in these studies was not on comparing alternate behavioural frameworks. Moreover, although qualitative in nature, subjective factors which significantly influence the choice behaviour (Srinivasan, Naidu & Pradhan, 2007) have not been evaluated in these studies on behavioural frameworks. Hence there is a need to study alternate decision rules, compare their performance and also evaluate the effect of subjective factors in each of these frameworks.

Due to the absence of comparative analysis, this study is motivated by the need to understand the extent to which mode choice involves non-compensatory behaviour, the degree of asymmetry between utility and disutility, role of risk aversion, regret and subjective factors, particularly in the Indian context. A better behavioural understanding using suitable modelling frameworks has the potential to lead to more accurate mode share forecasts and evaluation of urban transport plans and policies. The scope of the study is limited to mode choice of work trip based on data collected in Chennai city. The data was collected by conducting household interview survey for the Chennai city in the year 2007. The data had 967 valid observations and was found to be representative of the worker population in Chennai. The alternatives considered include: Two-wheeler, Car, Bus, Train, Intermediate Public Transport (IPT), Non-Motorized transport.

This study attempts to contribute to research on mode choice by comparing alternate behavioural frameworks representing distinct decision rules adopted by individuals. It establishes that users tend to adopt different decision rules for at least some variables.

2. Literature review

The discrete choice context is typified by a decision maker, alternatives under consideration, decision attributes, and a decision rule (BenAkiva & Lerman, 1985). Since these decision rules are unobserved to the modellers, it is conventional in modelling practices to assume a suitable decision rule in order to represent the choice making process. Most mode choice studies assume Random utility maximization (RUM) as the latent decision rule due to its analytical tractability and ability to describe trade-offs among various attributes. However, as discussed earlier, there are certain decision making traits which these RUM frameworks fail to address. Hence, there is a need to consider and evaluate alternate decision rules which can better characterize mode choice and a model structure representing these decision rules. Mode choice studies which have considered alternate decision rules are summarized in this section.

Apart from Utility maximization, there are also other decision rules which have completely different error structure from RUM but still are fully compensatory in nature. "Random disutility minimization" (RDM) is one such decision rule proposed by Srinivasan, Naidu and Sutrala (2009). In RDM, an individual is assumed to choose that alternative for which he perceives minimum disutility. However, unlike RUM, the error structure used in RDM is "negative of Gumbel" and hence the probability structure is different from MNL.

"Random regret minimization" (RRM), based on the regret theory, is a framework proposed by Chorus, Arentze and Timmermans (2007) which is semi compensatory in nature. When a decision maker chooses an alternative from a set of options, it is quite possible that a non-chosen alternative might perform better than the chosen one and hence would render some regret to the decision maker. So, the individual is assumed to minimize this potential regret when choosing among alternatives rather than maximizing his/her perceived utility. The concept of regret is operationalized in models through binary comparison of alternatives in terms of attributes.

The importance of subjective factors on mode choice has been recognized by some studies conducted mainly in U.S and Europe. However, compared to level-of-service variables, relatively fewer studies have examined the importance of subjective and attitudinal effects in mode choice even in developed countries. Algers, Hansen and Tegner (1974) has examined the role of comfort and convenience on mode choice through proxy variables such as seat availability and number of transfers. Koppelman and Lyons (1981) have proposed a latent variable approach based on factor scores to measure subjective variables and found them to be significant in mode choice. Forward (1998) reported noticeable differences in users rating of modes on various subjective beliefs such as freedom, safety, comfort, and anxiety. More recently, Johansson and Heldt (2006) reported that subjective ratings of comfort and flexibility are strong determinants of choice between bus, car, and train, but reliability and safety were not.

Summarizing, the RUM framework is incapable to represent some of the relatively latent decision making traits observed in choice decision. Thus there is a need to analyse alternate frameworks which are not fully compensatory in nature. Further, relatively fewer attempts have only been made to study the effect of subjective factors on mode choice in developing countries. Due to these motivating reasons, the broad objective of this study is to investigate the performance of **alternate behavioural frameworks for mode choice decisions of workers in Chennai city. The following sub-objectives are pursued:**

- To develop and implement mode choice models consistent with alternative behavioural frameworks.
- To investigate which explanatory variables are generic and alternative specific according to different behavioural frameworks.
- To analyse the effect of subjective factors using two scales: a continuous latent variable scale vs. original ordinal scale ratings obtained from the users.
- Compare the performance of the different behavioural frameworks in evaluating selected transportation policy scenarios.

3. Data Description

The above research issues are investigated using data obtained from a sample of 967 workers in Chennai city (Srinivasan, Naidu & Pradhan, 2007). The data were collected using face-to-face interviews at randomly sampled households. The data contained information regarding socio-economic characteristics and travel characteristics including mode choice, work distance, work location, attitudes regarding various modes etc. The data were verified to be representative of worker population in Chennai city in terms of socio-demographic characteristics. For e.g. the sample and population values of average household size were 4.37 and 4.51 respectively (Census 2001). The average age of a worker was found to be 36.9 for the sample and around 38 for the city. The average household income (Rs 15,527 vs Rs 14,500 estimated by National Council of Applied Economic Research Report) was also consistent between the sample and the population. The choice alternatives include: two-wheeler, four-wheeler, bus, train, paratransit (auto rickshaw, company bus and shared bus) and non-motorized modes (walk and bicycle). The paratransit modes together will be referred to as Intermediate public transport (IPT) for convenience.

Although 77% of the sample owned two-wheelers, this mode was chosen by only 43% of workers. Similarly, only 5.7% of workers opted to choose car, though 17% of sampled households owned a car. The modal shares for the other modes are as follows; bus – 20.5%, train – 16%, IPT – 9.4%, non-motorized modes – 5.4%. The sample indicates that bus carries a larger proportion of public transit share than train. The lesser share of non-motorized modes is probably because of longer work distance for most respondents.

Respondents were asked to rate subjective factors like comfort, safety, reliability, stress, cost, flexibility in departure time and multiple destinations of the alternatives on a Likert scale of 1 – 5 where 1 indicates poor and 5 indicates excellent performance. This perception rating of the subjective factors not only represents the experience of the service offered by each of the alternatives but could also reflect the expectation on the performance of these attributes. These expectations translate into the importance individuals may assign to these attributes. From these ratings it was found that decision makers perceive the travel cost of personal vehicles and IPT to be high. These ratings also provide an indication that users give high priority to reliability and comfort in public transit. These ratings may also reflect the risk averse behaviour of decision makers.

4. Methodology

The data thus collected was used to build choice models in order to compare behavioural frameworks representing alternate decision rules.

4.1 Frameworks representing alternate decision rules

As per RUM, decision makers are assumed to choose that alternative for which they perceive the maximum utility whereas RDM and RRM characterize the risk aversion of decision makers and hence try to minimize their disutility or regret in choosing an alternative respectively. However, it is possible that an individual may not be risk averse on all the attributes that are evaluated. In other words, an individual could use decision rules selectively for evaluating attributes. Hence, there is a need to classify attributes based on the decision rule used for evaluating them. Thus a composite framework representing both utility maximizing and risk averse behaviour of decision makers is proposed. Therefore; this study considers four distinct frameworks, two of which represent fully compensatory decision rule – RUM and RDM, and two others representing semi compensatory decision rule – RRM and CDR (Composite Decision Rule).

4.2 Formulation and estimation details of each framework

Following are the set of models

- Simple Multinomial logit (MNL) model for Random Utility Maximization (RUM).
- A model with a negative Gumbel error term assumption for the Random Disutility Minimization (RDM)
- A non-linear utility function with binary comparison of attributes for Random Regret Minimization (RRM).
- A combination of RUM and RRM for Composite Decision Rule.

The random utility U_i that an individual perceives for an alternative *i* is given by

$$U_i = \sum \beta_{im} X_{im} + \varepsilon_i \qquad \forall i = 1,2,.....j \tag{1}$$

where,

X_{im} is the value of the m^{th} attribute for the i^{th} alternative,

β_{im} is the corresponding coefficient, and

ε_i is the random component (error term) of this utility. For notational convenience no index is used to represent the decision maker.

In case of MNL, this error term is assumed to be Gumbel distributed. However, in case of RDM, this error term is assumed to be "negative of Gumbel" distributed and hence the resulting probability structure, derived using DeMorgan's law, was a series of MNL models. This makes the model free from IIA assumption. Both these models are fully compensatory. Proposed by Srinivasan, Naidu and Sutrala (2009), the RDM model structure could be understood in the following manner. Consider the random disutility, an individual perceives for an alternative *i* be D_i, which is negative of the random utility term in (1).

$D_i = -U_i$

In RDM,

P_i = Probability that i has lower disutility than other alternatives

$= \Pr(D_i \le D_j) \qquad \forall\, j = 1,2,\ldots\ldots.K,\ j \ne i$

$= 1 - \Pr(Di \ge \text{disutility of altleast one of the other alternatives})$

Supposing there are four alternatives *i, p, q, r,* then

$$P_i = 1 - \sum \Pr(D_i \ge D_p) + \sum \Pr(D_i \ge D_p \text{ and } D_i \ge D_q) - \sum \Pr(D_i \ge D_p \text{ and } D_i \ge D_q \text{ and } D_i \ge D_r) \tag{2}$$

which are a series of MNL models in themselves.

Unlike these models, the RRM has a non-linear utility structure (regret function) with binary comparison of attributes of the alternatives making it semi-compensatory in nature (Chorus et al., 2007). The error term in RRM is Gumbel distributed and hence the conventional MNL probability expression is used. The deterministic component of the potential regret that an individual experiences on choosing alternative i with respect to an attribute m is given by,

$R_{im} = \sum_{j=1}^{K} \ln\,(1 + \exp(\beta_{jm}X_{jm} - \beta_{im}X_{im}))$ and so the regret experienced on i with respect to all attributes is given by,

$$R_i = \sum_{j=1}^{K}\sum_{m=1}^{M} \ln\,(1 + \exp(\beta_{jm}X_{jm} - \beta_{im}X_{im})) \qquad \forall\, j \ne i \tag{3}$$

where,

R_i is the deterministic component of regret experienced by an individual on choosing ith alternative,
M is the set of attributes influencing the alternatives, and
K is the total number of alternatives.

The expression shows that the regret for an alternative i is basically an attribute wise comparison of its attributes with those of the rest of the alternatives. RRM fundamentally involves minimizing this potential regret for each alternative and a rational decision maker is expected to choose that alternative for which he perceives minimum regret.

The deterministic component of CDR is a combination of a linear utility expression and a non-linear regret structure. The combined composite utility C_i could be expressed as,

$$C_i = \sum_{j=1}^{K}\sum_{m=1}^{N} \ln\,(1 + \exp(\beta_{jm}X_{jm} - \beta_{im}X_{im})) + \sum_{m=N+1}^{M} \beta_{im}X_{im} + \varepsilon_i \tag{4}$$

and has a Gumbel error term. In order to build a CDR model, the attributes need to classified as to whether they are evaluated based on a regret minimizing criteria or utility maximizing criteria. In the above case, N attributes are regret based and remaining M-N attributes are utility based. This should be determined by a pair of Horowitz tests. Each test involves a comparison of two models. In the first test, one model is a pure RUM model and the other one is a RUM model with only the attribute to be tested as regret based. In this test, the null hypothesis is that the attribute is utility based. In the second test, null hypothesis model would be pure RRM model and the other one would be a RRM model with the test variable as utility based. If both these tests led to the same conclusions, then the attribute could be classified as regret/utility based (Chorus et al., 2013).

Models, representing each of these frameworks, were built with the subjective factors on an ordinal scale. Since regret minimization framework involves binary comparisons of alternatives, the attributes have to be continuous and not ordinal. Hence, there is a need to convert the subjective factors (ordinal in nature) like perceptional rating on comfort, safety, reliability etc. of different alternatives into a continuous scale. This continuous latent variable was developed using an ordered response model, considering the subjective factors to be dependent upon trip parameters, personal or household level characteristics and perception of network performance. The effect on mode choice with both ordinal and continuous scales of subjective factors was compared. All these models are estimated using Maximum Likelihood Estimation (MLE) technique and their coefficients, t-stats and log likelihood values are obtained.

5. Results

This section summarizes the results and findings corresponding to research issues in context with the objectives identified earlier. These research issues are as follows:

- Do semi-compensatory decision rules simulate individual's mode choice decision making behavior better than fully compensatory decision rules?
- Do decision makers adopt different decision rules to evaluate different attributes?
- Does use of continuous latent variable for subjective factors provide significant improvement to the mode choice models over ordinal user ratings?
- How does variable sensitivity/elasticity vary across these frameworks?

In order to address these issues, the models that were built are RUM-MNL, RDM, RRM – MNL and CDR-MNL. Variables that were empirically logical and statistically significant were included in the model. These explanatory variables considered include level of service factors like travel time and travel cost, vehicle ownership levels, subjective factors like perceptional ratings on comfort, safety, reliability, ease of access and work related factors like work distance and presence of work related travel. In case of CDR, the attributes had to be classified based on the decision rule of evaluation. Only attributes that vary across alternatives like subjective factors and level-of-service factors were tested. Attributes that do not vary across alternatives like vehicle ownership levels and work related factors were considered utility based (because regret based evaluation is logical only for attributes that vary across alternatives). The **Table 1** consolidates the conclusions of this analysis. Data provided evidence to show that all the attributes which vary across alternatives were evaluated on a regret minimizing criteria except ease of rail access. It was inferred to be evaluated on a utility maximizing principle. Hence the CDR was built by considering attributes invariant across alternatives along with ease of rail access to be utility based and the remaining attributes to be regret based.

Table 1 Analysis to determine decision rule used to evaluate attributes varying across alternatives

Attribute tested	**Horowitz test inference considering attribute to be Utility based in RRM**	**Horowitz test inference considering attribute to be Regret based in RUM**	**Conclusion**
Comfort	Regret	Regret	Regret
Safety	Regret	Regret	Regret
Reliability	Regret	Regret	Regret
Ease of train access	Utility	Utility	Utility
Travel time	Regret	Regret	Regret
Travel cost	Regret	Regret	Regret

The **Table 2** summarizes the model coefficients, log likelihood and likelihood ratio indices of all the four models (RUM-MNL, RDM, RRM – MNL and CDR-MNL). It shows that the models representing semi-compensatory decision rules (CDR: -872.13, $\rho^2 = 0.497$ and RRM: -879.96, $\rho^2 = 0.492$) outperform the fully compensatory decision rule models (RUM: -882.05, $\rho^2 = 0.491$ and RDM: -881.21, $\rho^2 = 0.491$) in terms of log likelihood points and ratio indices. Further, it also shows the superior performance of CDR with respect to all the other frameworks (Pure RUM, Pure RDM and Pure RRM). Since the models are non-nested, the Horowitz test could be used to compare the models statistically.

The CDR model is compared with the other three models in this test. The test results (test statistic $\Phi(-4.63)$ for RUM, Φ (-4.41) for RDM and $\Phi(-4.02)$ for RRM, where Φ represents the CDF of the standard normal distribution, all $<<0.001$) provides evidence to reject the null hypothesis that a decision maker would adopt one and only one decision rule to evaluate different attributes. In other words, an individual would tend to use different decision rules to gauge different attributes to choose the best alternative. Further, these models also differ in terms of their specification with respect to subjective factors. All the models had mode specific comfort coefficients for both two-wheeler and car. Safety coefficient was alternate specific for car and bus in CDR model whereas generic in the rest of the models. Reliability

Table 2 Models for alternate behavioral frameworks

Variable Explanation	**RUM-MNL**	**RDM**	**RRM-MNL**	**CDR-MNL**
Alternate specific constants	**Coeff (t-stat)**	**Coeff (t-stat)**	**Coeff (t-stat)**	**Coeff (t-stat)**
Two-wheeler constant	-2.97 (-1.78)	-2.95 (-2.04)	-0.59 (-0.51)	-1.65 (-0.58)
Car constant	-4.83 (-1.74)	-2.07 (-0.96)	-0.81 (-0.63)	-2.96 (-0.69)
Bus constant	2.80 (1.32)	2.06 (1.07)	-0.87 (-0.50)	-2.30 (-0.78)
Train constant	3.96 (6.22)	2.64 (4.90)	0.83 (1.87)	-0.46 (-0.16)
Non-motorized constant	13.67 (11.93)	9.80 (10.01)	10.59 (12.19)	13.79 (5.32)
Level of service factors				
Travel time	-0.04 (-8.46)	-0.03 (-6.95)	-0.01 (-2.57)	-0.01 (-2.60)
Two-wheeler travel cost	-0.19 (-12.22)	-0.14 (-10.53)	-0.05 (-3.13)	-0.05 (-3.03)
Car travel cost	-0.01 (-1.61)	-0.01 (-2.12)	-0.01 (-2.91)	-0.003 (-2.40)
Subjective factors				
Comfort in two-wheelers	8.81 (11.91)	6.84 (10.75)	4.74 (7.40)	7.32 (9.91)
Comfort in Cars	3.56 (2.52)	2.13 (1.94)	1.93 (2.33)	1.74 (2.20)
Safety in Cars	-	-	-	4.28 (3.08)
Safety in Bus	-	-	-	1.00 (2.49)
Safety in Car and Bus	4.09 (6.50)	2.70 (5.15)	0.50 (4.89)	-
Reliability in Bus	0.62 (2.13)	0.61 (3.36)	2.56 (5.06)	-
Reliability in Public transport	-	-	-	2.82 (8.44)
Reliability in IPT	-	-	-	1.65 (1.83)
Reliability in Train and IPT	4.68 (9.53)	3.47 (8.01)	1.57 (3.32)	-
Ease of access to train	1.49 (4.51)	1.12 (3.83)	0.55 (1.70)	0.39 (2.15)
Vehicle ownership levels				
2ws in the household (2w)	0.36 (2.80)	0.33 (2.87)	0.21 (1.69)	0.32 (2.45)
2ws in the household (4w)	-1.37 (-3.92)	-0.77 (-2.79)	-0.42 (-2.97)	-1.45 (-4.10)
4ws in the household (4w)	4.62 (8.68)	3.09 (9.89)	2.69 (5.10)	4.63 (8.63)
Work related factors				
Distance of work place from home	0.49 (4.21)	0.31 (4.30)	0.13 (4.13)	0.49 (4.12)
Presence of work related travel	0.99 (2.51)	0.68 (2.06)	0.30 (2.78)	1.04 (2.61)
Log- L(0)	-1732.63	-1732.63	-1732.63	-1732.63
Log-L(β)	-882.05	-881.21	-879.96	-872.13
ρ^2	0.491	0.491	0.492	0.497
Adjusted ρ^2	0.388	0.389	0.390	0.394
Number of parameters	20	20	20	21

Ordinal subjective ratings (model details)

Log-L(β)	-1052.69	-1046.74	-1033.50	-1061.08
ρ^2	0.392	0.396	0.404	0.388
Adjusted ρ^2	0.272	0.277	0.285	0.266

coefficient was generic for public transit (Bus and Train) and alternate specific for IPT in CDR model whereas it was alternate specific for bus and generic for train and IPT in the other models.

All the models that have been built are based on continuous latent subjective factors developed using an ordered response model from ordinal perceptional ratings. Therefore, there is a need to compare the performance of the model with ordinal ratings of subjective factors. The **Table 2** also shows the log likelihood values for the models with ordinal subjective factor ratings. Horowitz test was performed on all the models with the null hypothesis that model with ordinal ratings was better. The test results (test statistic Φ(-18.48) for RUM, Φ(-18.16) for RDM, Φ(-17.51) for RRM and Φ(-19.47) for CDR, all <<0.001) indicate that the models with continuous latent subjective factors performed better than ordinal perceptional rating based models.

All these findings have highlighted the difference of CDR from other models. However, none of these tests could detect substantial differences among RUM, RDM and RRM models. Although these models were found to be different in terms of the variable sensitivities, these values cannot be directly compared since each of these frameworks has varying utility (disutility or regret) structures, error terms and resulting probability definitions. Nevertheless, elasticities of the variables could be used to compare their sensitivities across models.

5.1 Findings from elasticities which vary across frameworks

The relative importance with which decision makers weigh subjective factors varies across frameworks. In both the semi-compensatory frameworks, RRM and CDR, decision makers seem to give greater importance to subjective factors in the following manner – *comfort on personal vehicles*, followed by *reliability, safety and ease of rail access*. However, in case of RUM and RDM, decision makers evaluate subjective factors in a different manner. In case of RUM, individuals give more importance to *comfort on personal vehicle,* then *safety on bus,* then *reliability with IPT and train,* followed by *safety on personal vehicles, ease of rail access and reliability with bus*. In RDM, the relative importance is higher for *comfort on personal vehicle,* then *safety on bus,* then *reliability with IPT and train,* followed by *safety on personal vehicle, ease of rail access and bus reliability*.

5.2 Findings from elasticities which are identical across frameworks

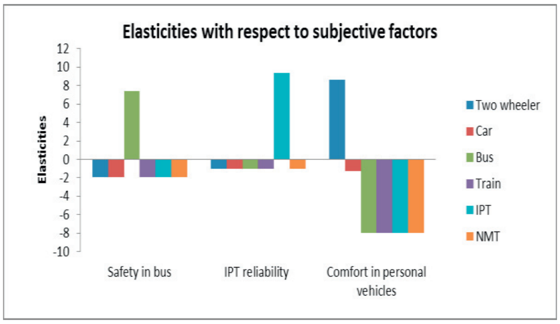

Fig.1. Elasticities with respect to some subjective factors

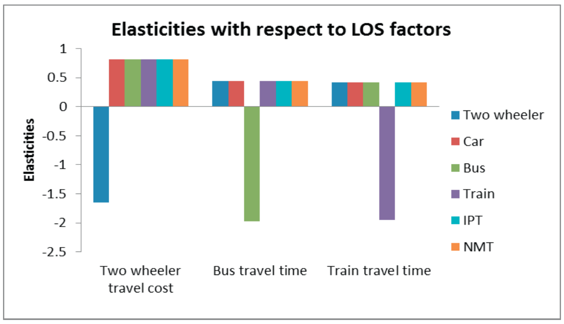

Fig.2. Elasticities with respect to some LOS factors

Comfort in personal vehicles, reliability in IPT and *Safety in bus* were found to be the most influential variables on mode choice in all the frameworks. There is, thus, a need to include the effect of subjective factors on mode choice since their influence seems to be to a greater extent than the most obvious determinants of choice like travel time and travel cost. Among LOS factors, *two-wheeler travel cost* and *travel time on public transit* (bus and train) were the most significant factors. **Fig 1 and Fig 2** depicts these findings graphically.

6. Policy analysis

The models developed were then applied with two sets of policy decisions implemented in recent years with regard to fuel price hike, bus and train fare changes. The first and second set of policy decisions are used to study the change in mode shares from 2007 to 2010 and 2007 to 2012 respectively. The petrol price hike from Rs 52 – Rs 62.5 and distance based slab fares for bus (both implemented in 2010) constitutes the first scenario. Second scenario includes fuel price hike from Rs 52 – Rs 73.16, distance based slab fares for bus and a distance based new slab fares for train (all implemented in 2012). This new slab fare for trains begin from Rs 5 for the first 20 kms of travel distance and increments by Rs 5 for every additional 20 kms. The modal shares were forecasted for both the scenarios using all the models and are tabulated in **Tables 3 and 4**. The corresponding changes in modal share (%) are shown in **Figs 3 and 4**.

The results of the policy analysis imply that there is a 3-4% decrease in two-wheeler share and negligible changes in car and non-motorized shares for the first scenario. A small increase of approximately 1% is observed for bus, Train and IPT. The second scenario shows around 8% decrease in two-wheeler share and less than 1% increase in car and non-motorized shares. It also shows considerable increase of around 1-2.5% for bus, 2.5-3.5% for train and 2-4% for IPT.

Notable differences were also observed across the frameworks in both the scenarios. Both the regret based models forecasted relatively lower two-wheeler, IPT and non-motorized shares than utility and disutility based models. However, the disutility based model showed lesser decrease in shares than other models for both bus and train.

When comparing the change in mode shares of different frameworks, with respect to RUM, all other frameworks have lesser (**<** 1%) increase in train shares in both the scenarios. For IPT, the increase in shares of all the frameworks is on a higher side than RUM for the first scenario (< 0.6%). This trend is however completely reversed in the second scenario (<2%). In case of bus shares, the increase in shares is comparable for all the frameworks in the first scenario and more (2% for RDM, 3% for CDR and 4% for RRM) for all other frameworks with respect to RUM in the second scenario.

Table 3 Base and forecasted modal shares (%) for first scenario

Modes	**Model**	**RUM**	**RDM**	**RRM**	**CDR**
	Base	**Scenario**	**Scenario**	**Scenario**	**Scenario**
Two-wheeler	43.0	39.4	39.3	39.8	39.7
Car	5.8	6.0	5.8	5.7	5.9
Bus	20.5	21.7	21.7	21.7	21.6
Train	15.9	17.0	16.6	17.1	17.0
IPT	9.4	10.1	10.7	10.2	10.3
NMT	5.4	5.8	5.9	5.5	5.5

Table 4 Base and forecasted shares (%) for second scenario

Modes	**Model**	**RUM**	**RDM**	**RRM**	**CDR**
	Base	**Scenario**	**Scenario**	**Scenario**	**Scenario**
Two-wheeler	43.0	34.6	34.7	35.0	35.0
Car	5.8	6.4	6.2	5.6	6.2
Bus	20.5	19.4	21.4	23.1	22.5
Train	15.9	19.5	18.6	18.7	18.6
IPT	9.4	13.5	12.7	11.7	11.8
NMT	5.4	6.6	6.4	5.9	5.9

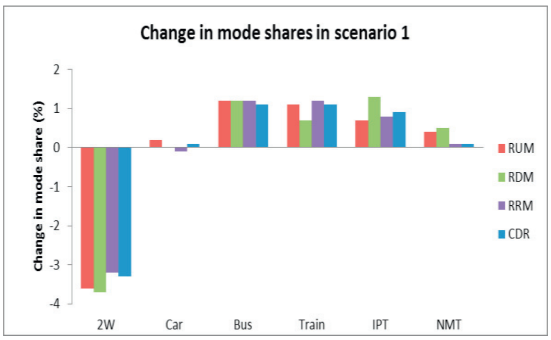

Fig.3. Change in modal shares (%) for first scenario

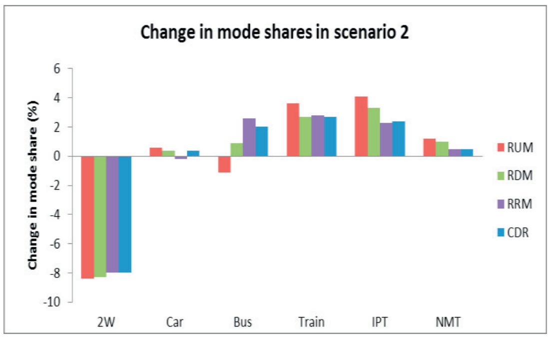

Fig.4. Change in modal shares (%) for second scenario

7. Summary and Conclusions

The following salient findings are noteworthy:

- The modelling results suggest that semi-compensatory frameworks provide a better behavioural representation than fully compensatory ones for the observed data since both RRM and CDR frameworks were statistically superior to RUM and RDM frameworks. Also, CDR performs better than the RRM, suggesting that some attributes are evaluated based on regret criterion, and others based on utility maximization.
- Contrary to conventional models, where all variables are assumed to be fully compensatory, almost all choice variant attributes were found to be evaluated using regret except subjective rating for *train access*.
- The sensitivity to subjective factors was found to be significantly varying across alternatives as well as across the frameworks. The use of continuous latent variable for subjective factors provided a significant improvement to the mode choice models over use of ordinal ratings.
- The policy evaluation results also differ based on the different frameworks used. The regret based models lead to smaller changes in two-wheeler, IPT and non-motorized shares than utility and disutility based frameworks. Disutility models tend to predict lesser reduction in public transit shares (both bus and train) than other models. All models, show negligible changes in car mode share for the policy scenarios considered.

These findings have important implication for mode choice estimation and urban transport policy evaluations in Indian cities. This study is based on the work trips of workers in Chennai city. It would be interesting to study the non-mandatory trips of workers and trips of non-workers. The socio-demographics, land use and the transportation infrastructure would be completely different in other cities when compared to Chennai, which would add to the variation in the behaviour of the trip makers. This is also a potential direction for further research in this context. The analysis in this study is at trip level of an individual and not at tour level. Further, neither activity characteristics of an individual nor intra-household interactions and the corresponding travel behaviour has been taken into consideration. Studies, based on data to this extend, can yield much more useful behavioural insights with reference to mode choice. This analysis considers alternatives to be completely independent of each other, which need not be the case in reality. Hence, studying mode choice behaviour considering the alternatives to be correlated could also provide interesting results.

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